In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import timeit
from scipy.stats import zscore
```

In [2]:
```
full_data_B=pd.read_csv("DataB.csv")
```

In [3]:
```
full_data_B
```

Out[3]:

	Unnamed: 0	fea.1	fea.2	fea.3	fea.4	fea.5	fea.6	fea.7	fea.8	fea.9	...	fea.776	fea.777	f
0	1	4	4	3	0	0	4	2	1	4	...	1	3	
1	2	5	1	4	3	1	3	5	1	4	...	1	1	
2	3	1	3	0	3	1	1	0	1	0	...	3	0	
3	4	5	3	2	3	5	2	2	0	4	...	5	4	
4	5	3	5	3	3	0	4	1	1	4	...	1	3	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2061	2062	4	0	3	0	4	0	4	3	1	...	0	1	
2062	2063	2	2	3	4	2	1	2	3	3	...	4	0	
2063	2064	2	3	2	3	1	2	5	5	5	...	5	1	
2064	2065	5	2	4	3	1	0	3	2	2	...	3	2	
2065	2066	3	3	1	3	2	5	4	2	2	...	2	3	

2066 rows × 786 columns

In [4]:
```
features_data_B=full_data_B.filter(regex=("fea.*"))
```

In [5]:
```
features_data_B
```

Out[5]:

	fea.1	fea.2	fea.3	fea.4	fea.5	fea.6	fea.7	fea.8	fea.9	fea.10	...	fea.775	fea.776	fea.7
0	4	4	3	0	0	4	2	1	4	1	...	1	1	
1	5	1	4	3	1	3	5	1	4	4	...	3	1	
2	1	3	0	3	1	1	0	1	0	2	...	4	3	
3	5	3	2	3	5	2	2	0	4	5	...	4	5	
4	3	5	3	3	0	4	1	1	4	3	...	1	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2061	4	0	3	0	4	0	4	3	1	2	...	3	0	
2062	2	2	3	4	2	1	2	3	3	4	...	1	4	
2063	2	3	2	3	1	2	5	5	5	0	...	3	5	
2064	5	2	4	3	1	0	3	2	2	1	...	2	3	
2065	3	3	1	3	2	5	4	2	2	4	...	3	2	

2066 rows × 784 columns

In [6]:
```
features_data_B_znorm=features_data_B.apply(zscore)
```

In [7]:
```
features_data_B_znorm
```

Out[7]:

	fea.1	fea.2	fea.3	fea.4	fea.5	fea.6	fea.7	fea.8	
0	1.010077	0.966782	0.359594	-1.668004	-1.638671	1.007994	-0.324102	-0.992537	0.9
1	1.687176	-1.029924	1.026488	0.336317	-0.976018	0.340307	1.674690	-0.992537	0.9
2	-1.021220	0.301213	-1.641090	0.336317	-0.976018	-0.995067	-1.656630	-0.992537	-1.6
3	1.687176	0.301213	-0.307301	0.336317	1.674594	-0.327380	-0.324102	-1.648724	0.9
4	0.332978	1.632350	0.359594	0.336317	-1.638671	1.007994	-0.990366	-0.992537	0.9
...	...	...	...	...	...	...	...	...	
2061	1.010077	-1.695492	0.359594	-1.668004	1.011941	-1.662753	1.008426	0.319835	-1.0
2062	-0.344121	-0.364355	0.359594	1.004424	-0.313365	-0.995067	-0.324102	0.319835	0.3
2063	-0.344121	0.301213	-0.307301	0.336317	-0.976018	-0.327380	1.674690	1.632208	1.6
2064	1.687176	-0.364355	1.026488	0.336317	-0.976018	-1.662753	0.342162	-0.336351	-0.3
2065	0.332978	0.301213	-0.974195	0.336317	-0.313365	1.675681	1.008426	-0.336351	-0.3

2066 rows × 784 columns

KPCA

In [8]:
```
start = timeit.default_timer()
```

In [9]:
```
from sklearn.decomposition import KernelPCA
k_pca = KernelPCA(n_components=2, kernel='rbf',random_state=42)
k_pca_transformed=k_pca.fit_transform(features_data_B_znorm)
```

In [10]:
```
stop = timeit.default_timer()
print('Time KPCA: ', stop - start)

Timetaken = pd.DataFrame(columns = ['Model', 'time'])
Timetaken = Timetaken.append({'Model':'KPCA', 'time':stop-start},ignore_ind
ex=True)
```

```
Time KPCA:  2.807220315000002
```

In [11]:
```
Timetaken
```

Out[11]:

	Model	time
0	KPCA	2.80722

In [12]:
```
k_pca_transformed_df=pd.DataFrame(k_pca_transformed)
```

In [13]:
```
k_pca_transformed_df['gnd']=full_data_B.gnd
```

In [14]:
```
k_pca_transformed_df
```

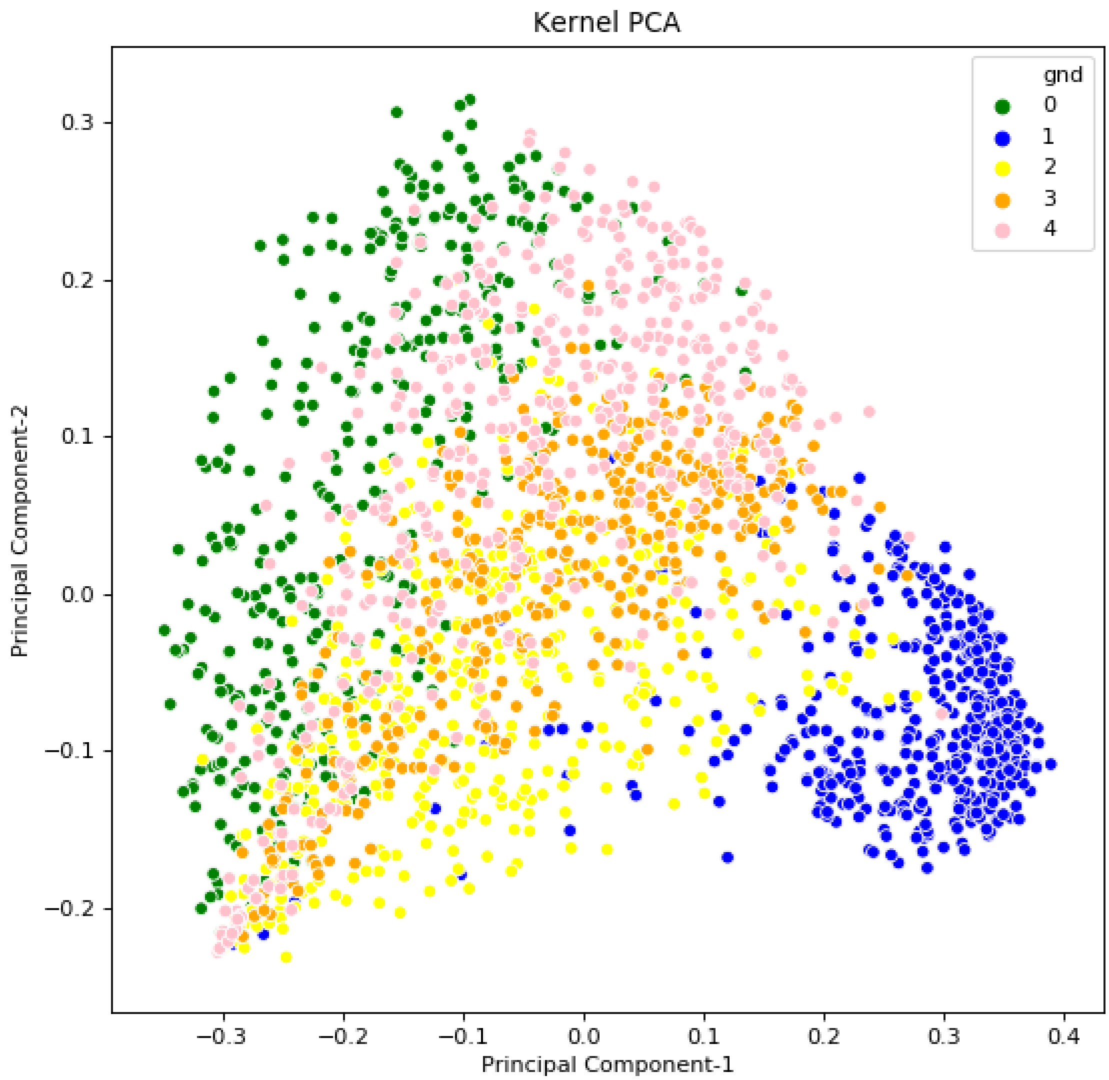
Out[14]:

	0	1	gnd
0	-0.141733	0.157522	0
1	-0.176054	0.096747	0
2	-0.075397	0.147357	0
3	-0.130459	0.173384	0
4	-0.296012	0.041533	0
...	...	...	...
2061	0.074913	0.209512	4
2062	-0.041609	0.093795	4
2063	0.051968	0.246317	4
2064	0.141469	0.157865	4
2065	0.100770	0.069533	4

2066 rows × 3 columns

In [15]:
```
fig=plt.figure(figsize=(8, 8), dpi= 80)
sns.scatterplot(x=k_pca_transformed_df[0],y=k_pca_transformed_df[1],hue=k_p
ca_transformed_df.gnd,legend='full',palette=['green','blue','yellow','orang
e','pink'])
plt.xlabel('Principal Component-1')
plt.ylabel('Principal Component-2')
plt.title('Kernel PCA')
```

Out[15]:
```
Text(0.5, 1.0, 'Kernel PCA')
```



ISOMAP

In [16]:
```
start = timeit.default_timer()
```

In [17]:
```
from sklearn.manifold import Isomap
iso = Isomap(n_components=2)
iso_transfer= iso.fit_transform(features_data_B_znorm)
```

In [18]:
```
stop = timeit.default_timer()
print('Time ISOMAP: ', stop - start)

Timetaken = Timetaken.append({'Model':'ISOMAP', 'time':stop-start},ignore_i
ndex=True)
```

```
Time ISOMAP:  16.555946204
```

In [19]:
```
Timetaken
```

Out[19]:

	Model	time
0	KPCA	2.807220
1	ISOMAP	16.555946

In [20]:
```
iso_transfer_df=pd.DataFrame(iso_transfer)
```

In [21]:
```
iso_transfer_df['gnd']=full_data_B.gnd
```

In [22]:
```
iso_transfer_df
```

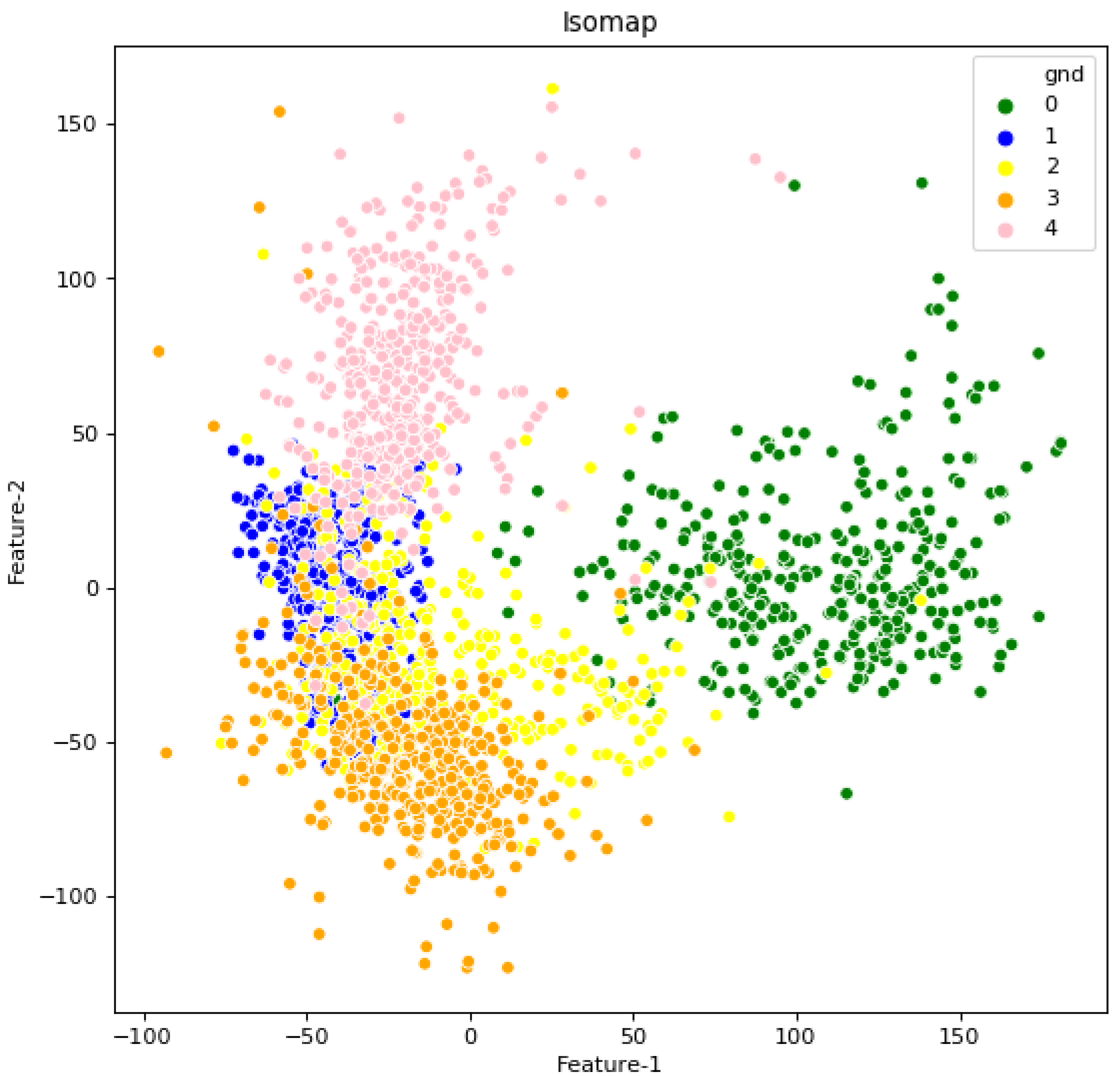
Out[22]:

	0	1	gnd
0	129.766248	-31.203243	0
1	142.147366	-21.099824	0
2	55.245085	-1.532745	0
3	102.802361	-13.649969	0
4	157.263819	-4.914420	0
...	...	...	...
2061	-21.316966	88.201528	4
2062	0.216036	113.891720	4
2063	-17.198930	51.483605	4
2064	-35.585489	52.963544	4
2065	-55.722457	59.996681	4

2066 rows × 3 columns

In [23]:
```
fig=plt.figure(figsize=(8, 8), dpi= 80)
sns.scatterplot(x=iso_transfer_df[0],y=iso_transfer_df[1],hue=iso_transfer_
df.gnd,legend='full',palette=['green','blue','yellow','orange','pink'])
plt.xlabel('Feature-1')
plt.ylabel('Feature-2')
plt.title('Isomap')
```

Out[23]:
```
Text(0.5, 1.0, 'Isomap')
```



Locally Linear Embedding

In [24]:
```
start = timeit.default_timer()
```

In [25]:
```
from sklearn.manifold import LocallyLinearEmbedding
lle_embed = LocallyLinearEmbedding(n_components=2,random_state=42)
lle_transformed = lle_embed.fit_transform(features_data_B_znorm)
```

In [26]:
```
stop = timeit.default_timer()
print('Time LLE: ', stop - start)

Timetaken = Timetaken.append({'Model':'LLE', 'time':stop-start},ignore_inde
x=True)
```

```
Time LLE:  11.347732464000003
```

In [27]:
```
lle_transformed_df=pd.DataFrame(lle_transformed)
```

In [28]:
```
lle_transformed_df['gnd']=full_data_B.gnd
```

In [29]:
```
lle_transformed_df
```

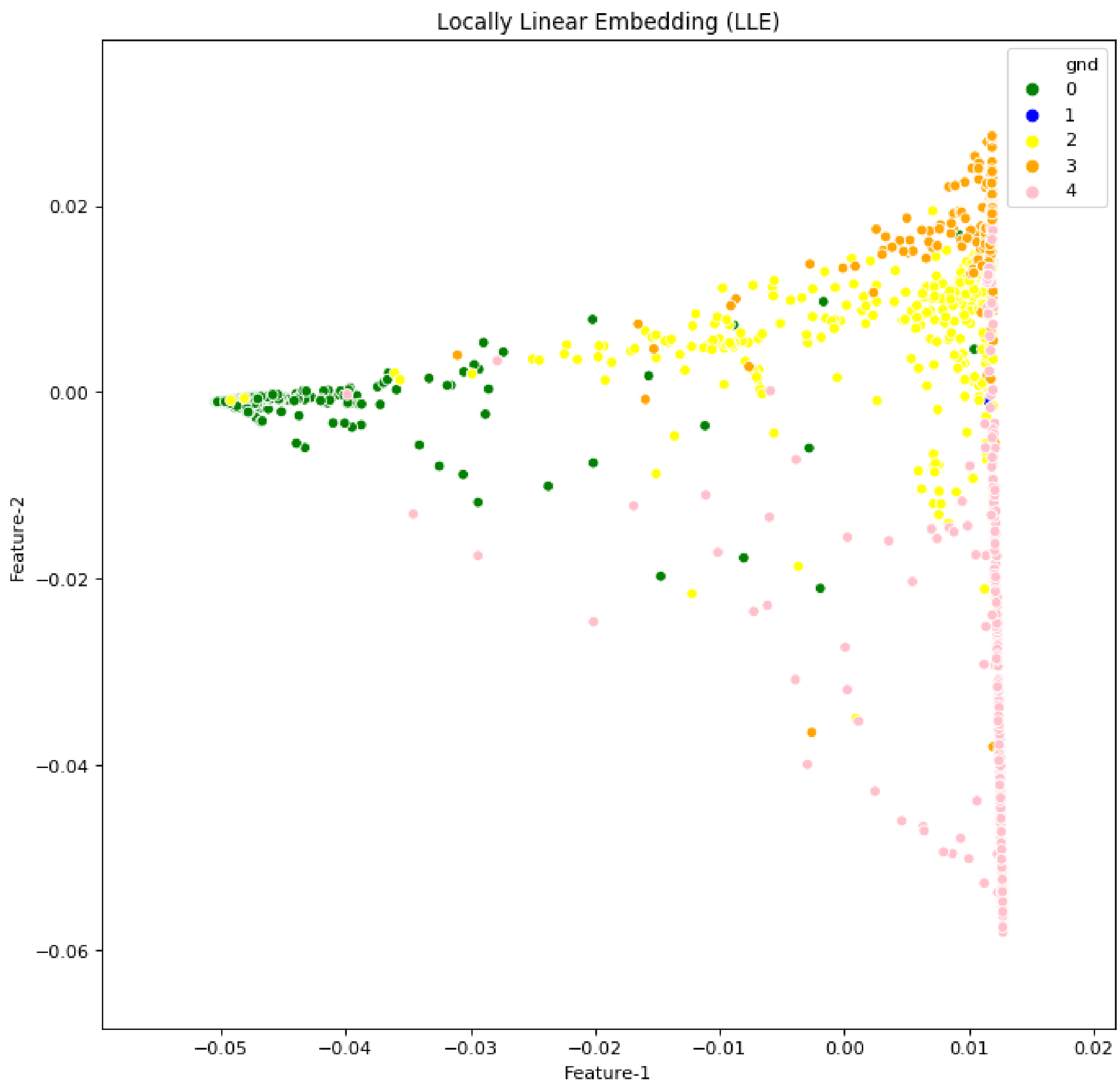
Out[29]:

	0	1	gnd
0	-0.047242	-0.000739	0
1	-0.046820	-0.000765	0
2	-0.040533	-0.000327	0
3	-0.044592	-0.000642	0
4	-0.047952	-0.000848	0
...	...	...	...
2061	0.012675	-0.053682	4
2062	0.012665	-0.052356	4
2063	0.012522	-0.043606	4
2064	0.012279	-0.031673	4
2065	0.012324	-0.035340	4

2066 rows × 3 columns

In [30]:
```
fig=plt.figure(figsize=(10, 10), dpi= 80)
sns.scatterplot(x=lle_transformed_df[0],y=lle_transformed_df[1],hue=lle_tra
nsformed_df.gnd,legend='full',palette=['green','blue','yellow','orange','pi
nk'])
plt.xlabel('Feature-1')
plt.ylabel('Feature-2')
plt.title('Locally Linear Embedding (LLE)')
```

Out[30]:
```
Text(0.5, 1.0, 'Locally Linear Embedding (LLE)')
```



In [ ]:

SPECTRAL EMBEDDING

In [31]:
```
start = timeit.default_timer()
```

In [32]:
```
from sklearn.manifold import SpectralEmbedding
spec_embed = SpectralEmbedding(n_components=2,random_state=42)
spec_transformed= spec_embed.fit_transform(features_data_B_znorm)
```

In [33]:
```
stop = timeit.default_timer()
print('Time Spectral: ', stop - start)

Timetaken = Timetaken.append({'Model':'SPECTRAL', 'time':stop-start},ignore
_index=True)
```

```
Time Spectral:  13.08508205599999
```

In [34]:
```
spec_transformed_df=pd.DataFrame(spec_transformed)
```

In [35]:
```
spec_transformed_df['gnd']=full_data_B.gnd
```

In [36]:
```
spec_transformed_df
```

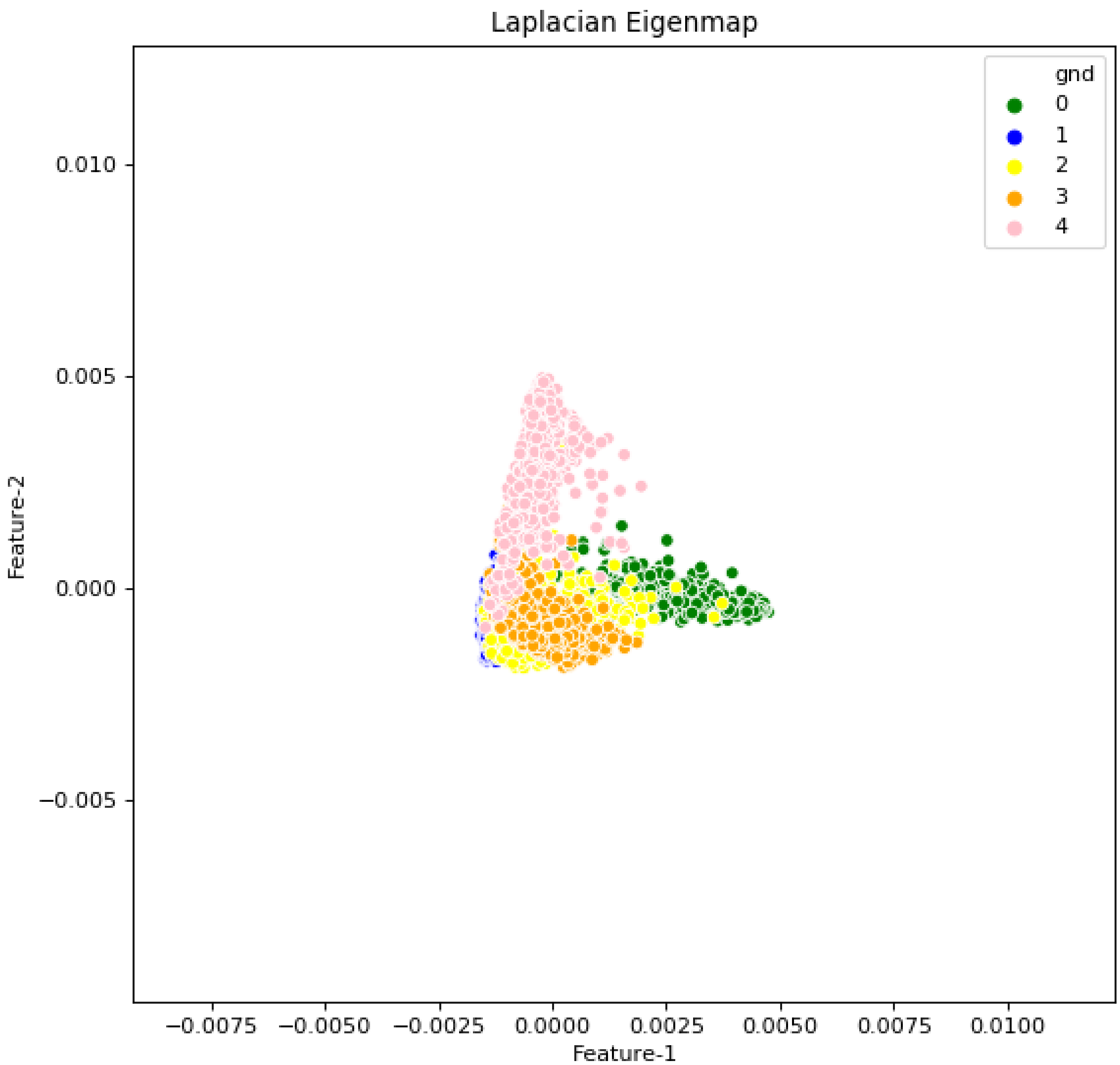
Out[36]:

	0	1	gnd
0	0.003813	-0.000506	0
1	0.003878	-0.000554	0
2	0.001921	-0.000458	0
3	0.002900	-0.000431	0
4	0.004274	-0.000675	0
...	...	...	...
2061	-0.000140	0.003128	4
2062	-0.000341	0.003527	4
2063	-0.000046	0.003117	4
2064	-0.000260	0.002440	4
2065	-0.000840	0.001530	4

2066 rows × 3 columns

In [37]:
```
fig=plt.figure(figsize=(8, 8), dpi= 80)
sns.scatterplot(x=spec_transformed_df[0],y=spec_transformed_df[1],hue=spec_
transformed_df.gnd,legend='full',palette=['green','blue','yellow','orange',
'pink'])
plt.xlabel('Feature-1')
plt .ylabel('Feature-2')
plt.title('Laplacian Eigenmap')
```

Out[37]:
```
Text(0.5, 1.0, 'Laplacian Eigenmap')
```



TSNE

In [38]:
```
start = timeit.default_timer()
```

In [39]:
```
from sklearn.manifold import TSNE
tsne_embed= TSNE(n_components=2,random_state=42)
tsne_transformed=tsne_embed.fit_transform(features_data_B_znorm)
```

In [40]:
```
stop = timeit.default_timer()
print('Time KPCA: ', stop - start)

Timetaken = Timetaken.append({'Model':'TSNE', 'time':stop-start},ignore_ind
ex=True)
```

```
Time KPCA:  39.5363964
```

In [41]:
```
tsne_transformed_df=pd.DataFrame(tsne_transformed)
```

In [42]:
```
tsne_transformed_df['gnd']=full_data_B.gnd
```

In [43]:
```
tsne_transformed_df
```

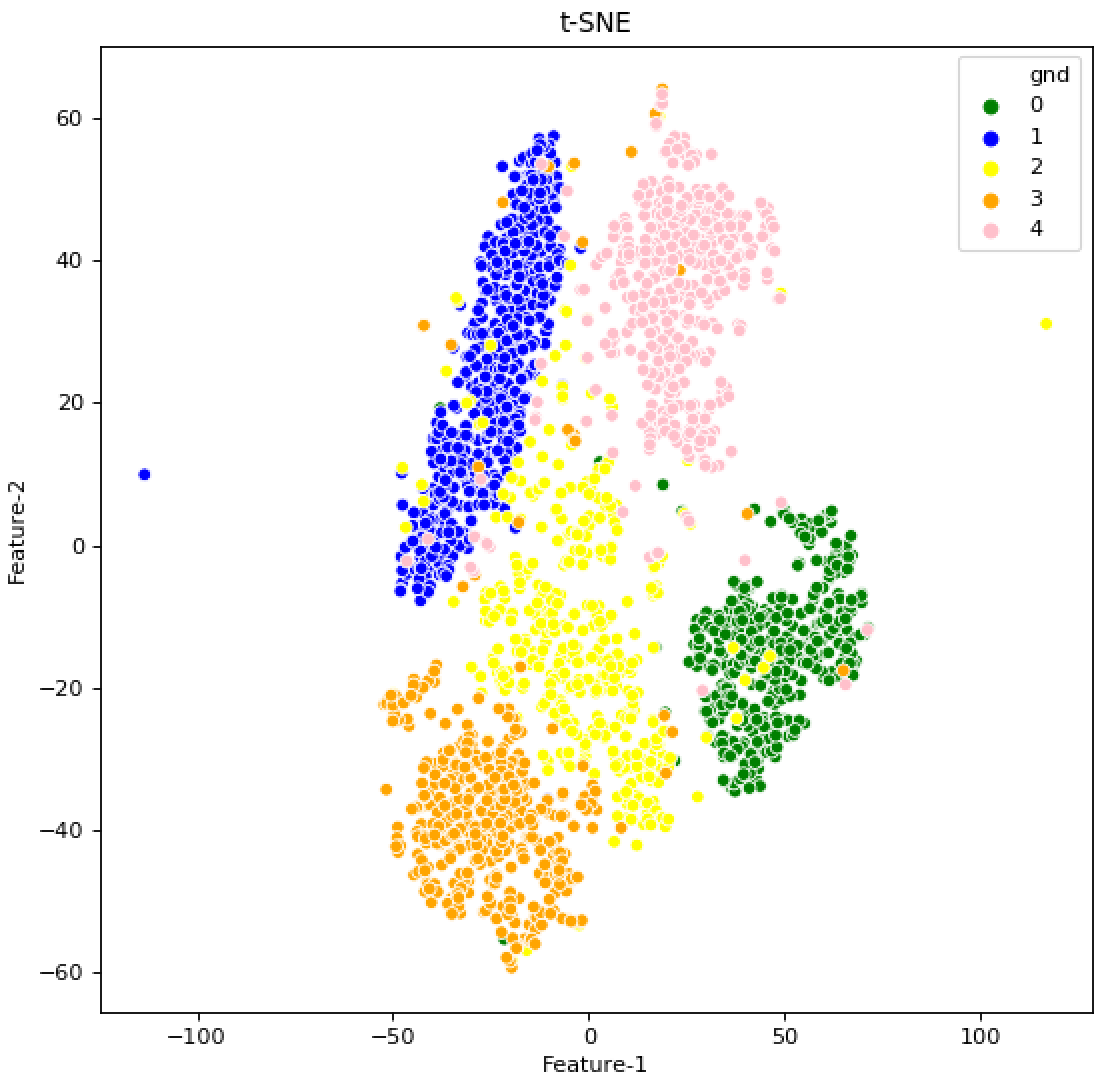
Out[43]:

	0	1	gnd
0	41.532661	-24.378746	0
1	41.793850	-26.211596	0
2	31.790344	-17.388863	0
3	31.795006	-21.673670	0
4	51.994953	-25.928551	0
...	...	...	...
2061	25.351837	53.300770	4
2062	33.663750	39.896450	4
2063	25.643785	33.787823	4
2064	11.307659	34.915760	4
2065	12.633137	49.038948	4

2066 rows × 3 columns

In [44]:
```
fig=plt.figure(figsize=(8, 8), dpi= 80)
sns.scatterplot(x=tsne_transformed_df[0],y=tsne_transformed_df[1],hue=tsne_
transformed_df.gnd,legend='full',palette=['green','blue','yellow','orange',
'pink'])
plt.xlabel('Feature-1')
plt.ylabel('Feature-2')
plt.title('t-SNE')
```

Out[44]: Text(0.5, 1.0, 't-SNE')



In [45]:
```
Timetaken
```

Out[45]:

	Model	time
0	KPCA	2.807220
1	ISOMAP	16.555946
2	LLE	11.347732
3	SPECTRAL	13.085082
4	TSNE	39.536396

ANALYSIS=>

1. Methods and Known class comparison:

KERNEL PCA

1.Class 1 is separated by component 1 along the 'x axes' whereas all the other classes are getting overlapped.

2.Component 2 isn't adding much information to the model along the y axes.

ISOMAP

1.Class clusters are made by isomap but there is a lot of overlapping between the classes.

2.class [0,4] are separated by both the components.

LLE

1.First component separates class [0,2] along the x axes.

2.Second component separates class [3,4] along y axes.

3.Class label 1 is heavily overlapped.

4.Both the components are adding decent information to the model.

LAPLACIAN EIGENMAP/SPECTRAL EMBEDDING

1.Variation within the whole data is minimized.

2.Distance between the clusters is also minimized.

3.Local clusters of class [0,1,3,4] are made whereas class label [2] is widely spread.

t-SNE

1.All the classes are separated very well by the components.

2.Well defined clusters are made which are separable along the x and y axes.

PERFORMANCE DIFFERENCES B/W t-SNE AND KERNEL PCA.

1.EXECUTION TIME:=>

a)t-SNE takes more execution time than all the other methods as well as much more than KERNEL PCA. time_taken by t-SNE=38.36 seconds.

b)KERNEL PCA takes less time than the t-SNE. In our case, it is 0.77 seconds which is drastically less than t-SNE.

c)In our case, time hardly matters because the dataset is not that big.

2.SEPARABILITY:=>

a)KERNEL PCA: The variation among all the data provided by the kernel pca is very high whereas no good clustering/separation between the classes can be seen.

b)T-SNE: The variation within the whole data is less than the kernel pca but the clustering is best.

OVERLAPPED DATAPOINTS:=>

1.kernel pca is overlapping a lot of datapoints of various classes whereas t-SNE segregates the class labels very well.

TRADEOFF:=>

Execution Time:

There is no need to consider the execution time in our dataset to find out the best method as the time taken by all the methods is in seconds as the dataset is not too large.

Separability:

The variation of data within the class and the variation of data between the classes is required to be considered in our method to properly classify the datapoints when any classification technique is applied. It can be clearly seen that t-SNE satisfies both of these tradeoffs providing the best clustering/local clusters for all the datapoints.

Citations:

1.https://blog.bioturing.com/2018/06/18/how-to-read-pca-biplots-and-scree-plots/

2.https://support.minitab.com/en-us/minitab/18/help-and-how-to/modeling-statistics/multivariate/how-to/principal-components/interpret-the-results/all-statistics-and-graphs/

3.https://distill.pub/2016/misread-tsne/